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13. ABSTRACT *(Maximum 200 words)*
During this period this grant partially supported 6 researchers, and resulted in over 21 publications. This unusually large activity is largely due to the enthusiasm of the researchers and their institution, Drexel University, which indirectly carried some of the financial burden.
Neural or other learning architecture for real world, real time applications, necessarily employ feedback and thus deal with the unavoidable dilemma of identification versus stabilization or tracking. The major finding reported focuses on this tradeoff and how to optimally perform it. For linear time invariant finite dimensional systems they are able to perform on-line closed loop identification and tracking. If in addition the learning and tracking cost functions are quadratic they show these costs may be linearly scalarized without loss of optimality.

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Hierarchical Neural Network (HNN) For Closed Loop Decision Making

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Contents

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This is the final report for the AFOSR grant #890010 which was granted for a period of two years starting on November 1988 and expiring on December 1993. It contributed to the publication of *54 !* articles of which *11* are archival and referred journals.

1. Accomplishments

The main accomplishments of the project are summarized as follows:

- Presenting and demonstrating the new concept of exploratory schedules. ([3,9,10,20,21,22,23,24,28,36,37,42]).

- Demostrating that even the preliminary version of Hierarchical Neural Network (HNN) has benefits not available to presently employed conventional methods. ([3,15,24,29]).

- A new theorem states constructive conditions for stable learning in closed loop. ([3,15,24]).

- Guaranteed stability in closed loop of HNN for a class of nonlinear systems linear in control [14,30].

- Application of the approach to several decision making problems: Robotics, Pattern Recognition, and Control. ([3,4,5,6,7,8,11,13,16,17,18, 19,23,25,26,27,28,32,33,35,41])

- A new cost function is postulated and an algorithm that employs this cost function is proposed for the learning of parameters [53].

2. Summary

The objectives of the project were to design and evaluate a hierarchical neural network (HNN) capable of real time learning and decision making in closed loop.

In the initial stages of the project the problem was defined and the relating state of the art methods were surveyed. Later control of a robotic system was used as the prototypical task and a HNN was designed and compared with the state of the art adaptive control techniques.

During this project the concept of exploratory schedules (ES) was developed [3,9,10,20,21,22,23,24,28,36,37,42]. ES is defined as system trajectories internally generated by the HNN for the purpose of efficient learning. This concept was implemented in an open-loop fashion for the control of robotic manipulators. A theorem was proved that gives constructive conditions for stable learing in closed loop [3,15,24,29]. This technique yielded improved transients in tracking desired trajectories in comparison with adaptive control methods. HNN architecture was applied as a controller for a class of nonlinear systems linear in control. It was shown to have guaranteed asymptotic stability [14,30]. HNN architecture was employed with partial success in areas of pattern recognition and control [4,5,6,7,8,11,13,18,19,25,26,27,32,33,35,41].

The newly proposed learning controller is shown in Figure 1. This learning controller consists of a standard adaptive controller and a learning loop that constitutes an additional block that updates the controller parameters from time to time [53].

The learning control algorithm consist of updating the parameter estimates as used in the controller. These parameters are selected from among a number of simulations runing in parallel. Each simulation is a model of the plant with different parameters. There are a total of (N+1) simulations, one simulation is the nominal simulation consisting of nominal parameters and the remaining N simulations consist of parameters in some neighborhood of

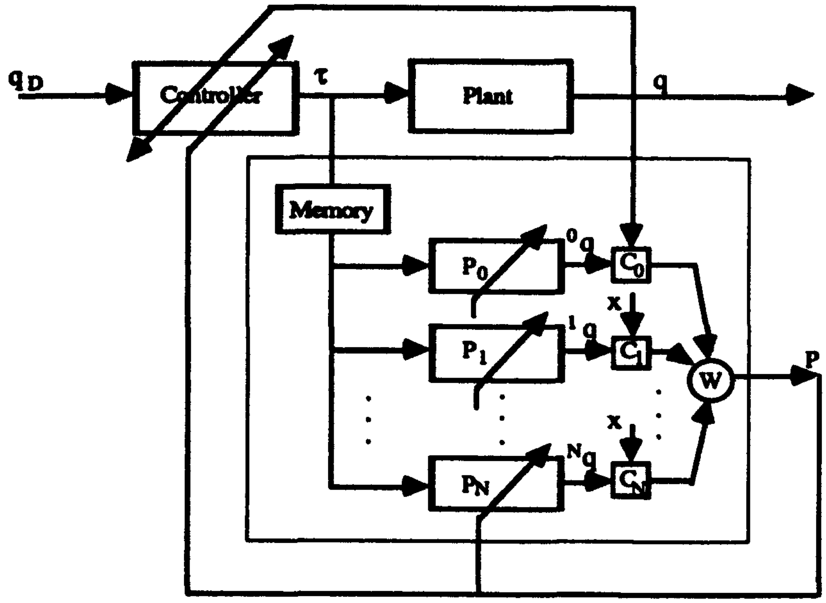

Figure 1: The learning control scheme

the nominal simulation. The scheme of selection of the parameters is facilated by using the costs, C_i, associated with each simulation. These costs are given by

$$C_i = \int_0^t || q - {}^iq ||_2 dt \qquad i \in \{0, 1, 2, ..., N\}$$

where ${}^iq$ = the state of the ith simulator.

3. Work in Progress

Currently we are engaged in finding the utility of the proposed cost function for a single degrees of freedom (DOF) manipulator and later for the general case. This entails in comparing the results obtained while minimizing the proposed cost function with the other learning type algorithms, such as based upon learning of iterative tasks [Kawamura-85], variable structure techniques, adaptive control methods, etc. For the purpose of such a comparison we are developing a software that will simulate these various methods in a user friendly environment.

4. Annual Technical Report submitted to AFOSR, November 1991.

Designing the Architecture of a Hierarchical Neural Network to Model Attention, Learning and Goal Oriented Behavior

I. Summary

This is a progress report for the AFOSR Grant # 890010 describing the research efforts undertaken during November 1990 through November 1991. During this period this grant partially supported 6 researchers, and resulted in over 21 publications. This unusually large activity is largely due to the enthusiasm of the researchers and their institution, Drexel University, which indirectly carried some of the financial burden.

Neural or other learning architecture for real world, real time applications, necessarily employ feedback and thus deal with the unavoidable dilemma of identification versus stabilization or tracking. The major finding reported below focuses on this tradeoff and how to optimally perform it. For linear time invariant finite dimensional systems we are able to perform on-line closed loop identification and tracking. If in addition the learning and tracking cost functions are quadratic, we show that these costs may be linearly scalarized without loss of optimality.

II. Objectives

The original objectives of the project were to design and evaluate a hierarchical neural network (HNN) capable of real time learning and decision making in closed loop, as described in the block diagram of figure 2.

BLOCK DIAGRAM

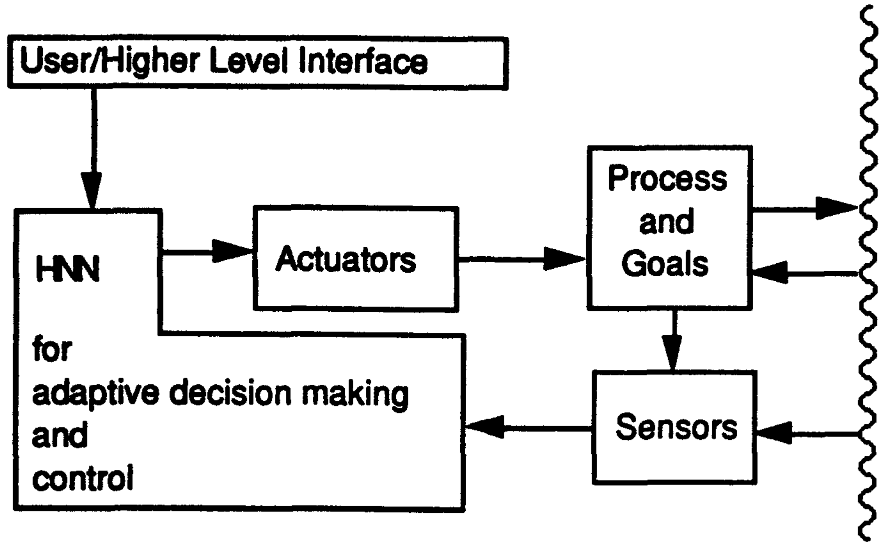

figure 2

The block diagram consists of:

- A process and goals which act on and are acted upon by the environment. The process, attainable goals, and environment are generally nonlinear, time varying and unknown or incompletely known.
- An interface to the User or another high level planner which specifies a set of tasks which are to be accomplished or goals which are to be met.
- A suitable set of sensors for determining the relevant states of the process and environment to carry out the request from the higher level planner.
- The HNN which provides the necessary adaptive decision making to carry out the task through assessment of the process and environment.
- A set of actuators which act on the process under the direction of the HNN.

III. Accomplishments

The projects' accomplishments are described as follows. The numbers of the sections of the desiderata as given in the report for the renewal of the grant are referenced in parentheses at the end of the subheadings.

A) Improved Design of Exploratory Schedules (A2)

Revisit Multiobjective Optimization for Functionals

In the optimization problem one is required to accomplish a number of tasks in some satisfactory manner. Furthermore, the tasks are usually conflicting, i.e. if we gain, in the sense of optimizing, for one task then we loose something for the other. In the case of aircraft design the tasks might be to improve the maneuverability and to achieve structural integrity at the same time. Another set of required tasks can be to minimize the drag while requiring to have the maximum capacity for the fuel tanks. Similarly, for the design of a missile, the different goals could be to achieve maximum distance with minimum fuel and shortest possible time.

As a usual practice the different cost functionals defined for each task are combined together via summation and the resulting coalesced scalar functional is optimized via standard optimization techniques. Such a coagulation results in a lump sum description of the achieved measure for the different criteria without any indication to the extent of relative quality achieved for each criteria.

However, we will be interested in such multiobjective optimization (MOOP) that will consider optimization of each individual criteria [Zadeh-63] in some sense of noninferiority called Pareto optimality. By Pareto optimality, in minimizing a number of functionals, a decrease in any one functional must lead to increase in some other functional. This therefore yields a range of arguments that give rise to the noninferior optimum set.

Therefore, the purpose of multiobjective optimization is to clearly identify the tradeoff achieved at the expense of the other criteria. This not only helps better understand the achieved tradeoff but also helps in the design of controllers by being able to operate within such a non-inferior optima. This is the crux of the multiobjective optimization problem.

Pareto optimal control problem is mostly solved via scalarization in order to obtain a single optimum. Among these approaches are *Utility functions Method* [Stadler -88], *Utopian Point Method* [Koussoulas-86], *Sequential optimization* [Stadler -88], *Goal programming* [Stadler -88], *Min-max*. Some other approaches are *Simultaneous Model-Matching Method* [Khargonekar-91], *Method of Proper Equality Constraints* [Lin-76], *General Theory for Optimal Processes* [Chang-66].

Closed Loop Identification via augmented state-parameter vector

In the existing identification algorithms the input and output of the plant are used to derived the parameters of the linear plant. The issue of state estimation is not considered as part of the identification / estimation process. These are the Least Square (LS) algorithms. The LS algorithms perform well in open loop. However, in closed loop their application have inherent problems as the feedback destroys the persistently exciting property of the input to the plant even if the input to the loop is persistently exciting.

The new approach is based on the observation that for control the plant's parameters as well as the states of the plant are required. Moreover, the new representation of linear time invariant systems presents the plant in such a form that the parameters appear linearly, thus enabling direct application of the well known observability theory. This is a generalization of the observability concept to identification of the plant's parameters. This simplicity comes at the expense that the new representation is time varying even if the original plant is time invariant. However, this is only a computational problem since the theory of observers for linear time-variant systems is well established. This approach requires less demanding conditions on the input to guarantee convergence of the estimates. In steady state it is sufficient for the input to be a sum of n distinct exponentials which is half of the quantity required in the common existing LS algorithms. Moreover, these conditions apply to estimation in open and closed loop *without any further* restrictions.

The final objective is to control the plant in closed loop. However, there is an inherent conflict between the control and the identification as they are competing for the only available resource, namely the input to the plant.

The Multiple Objective Optimization Theory is the framework that enables to formulate and to resolve these conflicting objectives. Namely, how to guarantee on one hand that the input to the plant will be sufficient for on-line identification and on the other hand that the tracking error will be small. This is clearly a subset of the learning versus tracking problem. Moreover, the concept of input that guarantees identification is a subset of the concept of exploratory schedule. It must be emphasized that the MOOP approach can not be satisfied with the existing LS identification algorithms as they fail to identify in closed loop. The new representation does not have this deficiency and enables to identify on line the plant while controling the plant in closed loop.

B) **Hardware and Neural Network Review** (B)

Many products are available in a variety of different forms.

1. <u>Software simulators</u>

   These are the most common and least expensive neurocomputing products.

   a) BrainMaker 2.1 by California Scientific Software (CSS).

   b) NeuroShell 4.0 by Ward Systems Group

c) AutoNet by Peak Software.

d) ANSim by SAIC.

e) NeuralWorks Professional II Plus by NeuralWare.

f) ExploreNet 3000 by HNC.

g) PLEXI by Lucid, Inc.

h) Braincel by Promised Land Technologies, Inc.

i) NNetSheet by Inductive Solutions, Inc.

j) Neuralyst 1.2

k) NDS 1000 by Nestor, Inc.

l) NeuroSym NeuroComputing Library in C.

m) OWL Neural Network Library by Olmsted & Watkins in C.

2. Accelerator Boards

a) BrainMaker C25 Accelerator Board.

b) NeuroBoard by Ward Systems Group's

c) Delta II Floating Point Processor by SAIC.

d) ANZA Plus Accelerator Board by HNC.

3. Integrated Circuits

a) Syntonic Systems Dendros-I.

b) Micro Devices MD1220.

c) Neural Semiconductors SU3232 and NU32.

d) Intel i80170.

e) Bell Laboratories IC.

f) Lockheed PNNP.

C) Application of Neural Network to Adaptive Control.

Necessary and Sufficient Conditions on the Observability and Identifiability of Linear Systems [50]

A new representation of linear time-invariant systems is presented. This representation enables to generate necessary and sufficient conditions on the simultaneous state observability and parameters identifiability of linear time-invariant systems. Sufficient conditions derived from the necessary and sufficient conditions are weaker than the well known persistent excitation conditions in the existing least square schemes. Namely, a sum of n distinct exponentials in the input to the system is sufficient. This is half of the quantity required in the common existing least square algorithms. These conditions apply to estimation in open and closed closed loop without further restrictions. Simulation results demonstrate the performance of estimation with this new approach.

Multiple Objective Optimization Approach to Adaptive and Learning Control [45]

This paper formulates a new approach to the classical learning/adaptive control problem. Our approach is based on two key observations: 1) the inherent conflict between control and identification as they are competing for the only available resource, namely the input to the plant; 2) when designing and optimizing the performance of a control system the current task as well as the repertoire of other typical future tasks which the system may encounter during its life time should be considered. Our approach is formulated for a general nonlinear time varying plant, thus, *unlike* existing adaptive control theory, the theory for linear time invariant system evolves as a special case of the general case. The design for the full life time of the system creates a methodology that specifies what current actions should be taken in addition to the tracking of the current reference trajectory, at the expense of some performance degradation in the current task, so as to improve the performance of future tasks, that is the learning tradeoff. The conflicting objectives, namely, tracking vs. learning and current task vs. future tasks, is most naturally posed and partially solved in the domain of Multiple Objective Optimization Theory. We demonstrate for linear time invariant plants with quadratic cost, that Pareto optimal learning adaptive controllers may be obtained by simple "out of loop" mixing, where a scalar controls the tracking vs. learning tradeoff in a reliable way.

On-Line Identification and Control of Linearized Aircraft Dynamics [46]

Standard Methods for on-line parameter identification generally require strong persistent excitation to achieve accurate results rapidly enough to be used in a closed loop control systems. Obviously, for manned aircraft, flying qualities can be significantly degraded if there is such a strong excitation present. Even with this excitation, identification may not be reliable for the closed loop flight control system since an effect of feedback is to damp out the disturbances that excite the system.

This paper examines a new approach for performing on-line identification and control that require substantially weaker excitation and will work even with closed loop systems. One key element of the approach used in this paper is a new representation of linear time-invariant systems that generalizes the observability concept to parameter identification and enables on-line identification in closed loop. This approach also uses separation theorems for nonlinear time varying systems that specify the exact conditions on the use of the certainty equivalence principle. A final key feature is the use of Multiple Optimization Theory to resolve the conflict between identification and controller performance as they compete for the only available resource, the inputs to the aircraft. Multiple Objective Optimization also allows the flight controller to utilize information available from future integrated systems, such as the Pave Pillar Architecture, to adjust the trade-off between identification and control to suit the current pilot task in a particular tactical/strategic situation.

In addition, the excitation sufficient for simultaneous parameters identification and state observation is half of that required with most existing Least Square algorithms.

In this paper, the approach is applied to a longitudinal model of a representative linearized high performance aircraft model. Simulation results compare the final controller with a conventional classical gain scheduled flight controller.

<u>On Generation of Exploratory Schedules In Closed Loop for Enhanced Machine Learning</u> [37]

Exploratory schedules (ES) are reference input trajectories designed to enhance the learning of system parameters. Such trajectories in general may not be the desired trajectories, resulting in larger tracking errors. However, ES offer faster convergence to the system parameters and therefore yield smaller long term tracking errors. The automation for the design of ES requires on-line modification of the desired trajectory to enhance learning at the expense of poorer initial tracking. We discuss this closed loop mode of generation of ES, and give an example of the benefits achieved by the utilization of ES in the context of controller design.

<u>A New Approach to Learning Control via Multiobjective Optimization</u> [31]

The material presented here is an extension to the previous work where estimation of the parameters of a plant was incorporated through Exploratory Schedules (ES) which are reference input trajectories designed to enhance the learning of system parameters. In the previous work ES were generated off-line and used in an open loop fashion. Moreover, these ES were used between actual control tasks therefore limiting the process of estimation during idle time. Here we present the approach to generate ES in a closed loop manner. Such trajectories in general may not be the desired trajectories, resulting in larger tracking errors. However, ES offer faster convergence to the system parameters and therefore yield smaller long term tracking errors. The automation for the design of ES requires on-line modification of the desired trajectory to enhance learning at the expense of poorer initial tracking.

Custom Neurocontroller for a Time Delay Process [43]

We propose a new neurocontrol architecture for time delay processes. The controller is based on a variable dimension adaptive model which is identified on-line, in closed loop. A nonlinear maximization procedure guarantees the minimal order of the employed model. A variety of control laws may be utilized in this new architecture. Simulations demonstrate the efficiency of the proposed controller.

Target Classification Using Radar Data: A Comparative Study [52]

This paper compares three different approaches when used against a problem of present and practical interest: the classification of radar return data from two classes of aircraft. The three approaches are: the typical feature extraction approach used for target classification when dealing with radar data; a multi layer perceptron neural network approach and; a branched multi layer perceptron neural network approach. The comparison was performed under equal conditions. The classification rate was used as the measure of effectiveness of the approach. The feature extraction approach provided a classification rate of 72.5%. The multi layer perceptron consisted of a one hidden layer network and the best classification rate it has provided is 85.1%. The branched multi layer perceptron consisted of two separate multi layer perceptron neural networks trained to recognize only one class of targets and the best classification rate it has provided is 54.9%.

D) Neurocontrol Test-Bed Design and Construction

A test-bed was constructed for the purpose of developing and testing Neurocontrol algorithms via control of a helicopter in flight. Conceptual and block diagrams of the flight control test bed in its present form are shown in figures 2 and 3. The test-bed consists of an electric powered radio control helicopter manufactured by the Kalt company which is mounted on a 6 DOF (degrees of freedom) flight stand. Sensing of the helicopters position and orientation is accomplished through six 5kΩ potentiometers which have been mounted at the joints of the flight stand. Currently four of the six joint position sensors are operational. Power is supplied to the helicopter's main motor, radio receiver and control servos via an umbilical to an external power supply. Flight control algorithm development is performed on an ALR 486 based computer. National Instruments LabWindows with 'C' is used as the program development environment. The helicopter's position as sensed by the potentiometers is transmitted via communication cable as a vector of varying voltages to a National Instruments NBMIO16 data acquisition board. The NBMIO16 provides the analog to digital conversion for the position sensing signals. The Airtronics VG6H radio transmitter that was provided with the helicopter was retained and a selection switch installed which allows control of the helicopter either manually via a test pilot or automatically through the flight control computer. The NBMIO16 performs the digital to analog conversion of the control signals to the transmitter. Subsystems of the flight control test-bed are currently being tested.

IV. Plan of Work for the 2nd Year

A) State of the Art in Finding the Pareto Set for MOOP

In the classical optimal control problem, different functionals are combined via summation to form a scalar functional and then that functional is optimized. Such a combination was only intuitive, and not based on sound mathematical analysis. The theory of multiobjective optimization with the specifics of Pareto optimality gives us the conditions under which we can achieve such a scalarization.

Usually when coupled costs are optimized there exists a region of tradeoff wherein one cost may be improved at the expense of others. Such a tradeoff is apparent in the problem of estimation verses control. At times the requirements for control may not be stringent and therefore, the cost related to estimation may be further decreased at the expense of the cost related to control in order to better the estimates, and vice versa. Therefore, the question that remains to be answered is how to achieve this tradeoff while remaining in the Pareto optimal region.

State of the art in multiobjective optimization deals with either obtaining a single noninferior point of operation or else concerns the generation of all the noninferior points. In the former case the tradeoff is explicit and fixed depending upon the type of multiple optimization procedure used to obtain the solution. The later case generates the whole Pareto set but since it is achieved via exhaustive search it is time consuming, and therefore not practical in a real time application.

B) Understand the Relations of MOOP to the On-line Tradeoff Between Identification and Tracking

In adaptive control the adaptation of parameters is achieved through laws based upon search in the gradient directions of the tracking error signal. These rules adapt the parameters such that the tracking of the desired trajectory is improved following an initial (possibly large) error transient. **However the system parameters may not be adapted to their true values.** Therefore, tracking is acomplished at the expense of identification. However, by using MOOP a tradeoff may be designed. This tradeoff is achieved via specification of functionals, one for the purpose of identification and the other for control. We expect that investigating the parameter adaptation properties as an effect of these functionals will lead to a better understanding of the adaptation process and therefore development of improved parameter adaptation laws.

C) Attempt to Solve the Landing Problem of a Helicopter as Suggested by Boeing

As part of our research into the state of the art in helicopter control systems, a meeting was arranged with a representative of Boeing Helicopter Co. The problem of automatically landing a helicopter onto a ship in rough seas was presented to us as one that is significant. Future efforts on this project are likely to be directed towards solving this problem. Conceptual and block diagrams of the proposed test-bed for investigation of the Rough Sea Landing Problem are shown in figures 4 and 5. The present helicopter flight control test bed will be augmented with 1) a robot manipulator and controller, and 2) additional sensing and computing resources. The robot manipulator is to be used to imitate the motion of a ship's landing platform. The type and quantity of additional sensors is currently being assessed.

V. Supported Researchers

Allon Guez, Ishak Bar-Kana, Ilan Rusnak, Ziauddin Ahmad, John Selinsky, Vadim Rokhlenko.

5. Publications

The following is a list of publications relevant to this project and/or partially supported by AFOSR grant# 890010.

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[18] Kumar, S., Guez, A., "Adaptive Pole Placement for Neurocontrol" International Joint Conference on Neural Networks 90, 1/90, Washington, D.C..

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